# Machine Learning and Data Mining

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Alma Mater Studiorum · University of Bologna

# Contents

# Acronyms

**BI** Business Intelligence

**DFM** Dimensional Fact Model

**DM** Data Mart

**DSS** Decision Support System

**DWH** Data Warehouse

**EIS** Executive Information System

**ERP** Enterprise Resource Planning

**ETL** Extraction, Transformation, Loading

**MIS** Management Information System

**OLAP** Online Analysical Processing

**OLTP** Online Transaction Processing

# 1 Introduction

## 1.1 Data

**Data** Collection of raw values. Data

**Information** Organized data (e.g. relationships, context, ...). Information

**Knowledge** Understanding information. Knowledge

### 1.1.1 Data sources

**Transaction** Business event that generates or modifies data in an information system (e.g. database). Transaction

**Signal** Measure produced by a sensor. Signal

**External subjects**

### 1.1.2 Software

**Online Transaction Processing (OLTP)** Class of programs to support transaction oriented applications and data storage. Suitable for real-time applications. Online Transaction Processing

**Enterprise Resource Planning (ERP)** Integrated system to manage all the processes of a business. Uses a shared database for all applications. Suitable for real-time applications. Enterprise Resource Planning

### 1.1.3 Insight

Decision can be classified as:

**Structured** Established and well understood situations. What is needed is known. Structured decision

**Unstructured** Unplanned and unclear situations. What is needed for the decision is unknown. Unstructured decision

Different levels of insight can be extracted by:

**Management Information System (MIS)** Standardized reporting system built on existing OLTP. Used for structured decisions. Management Information System

**Decision Support System (DSS)** Analytical system to provide support for unstructured decisions. Decision Support System

**Executive Information System (EIS)** Formulate high level decisions that impact the organization. Executive Information System

**Online Analysical Processing (OLAP)** Grouped analysis of multidimensional data. Involves large amount of data. Online Analysical Processing

**Business Intelligence (BI)** Applications, infrastructure, tools and best practices to analyze information. Business Intelligence

**Big data** Large and/or complex and/or fast changing collection of data that traditional DBMSs are unable to process. Big data

**Structured** e.g. relational tables.

**Unstructured** e.g. videos.

**Semi-structured** e.g. JSON.

**Anaylitics** Structured decision driven by data. Anaylitics

**Data mining** Discovery process for unstructured decisions. Data mining

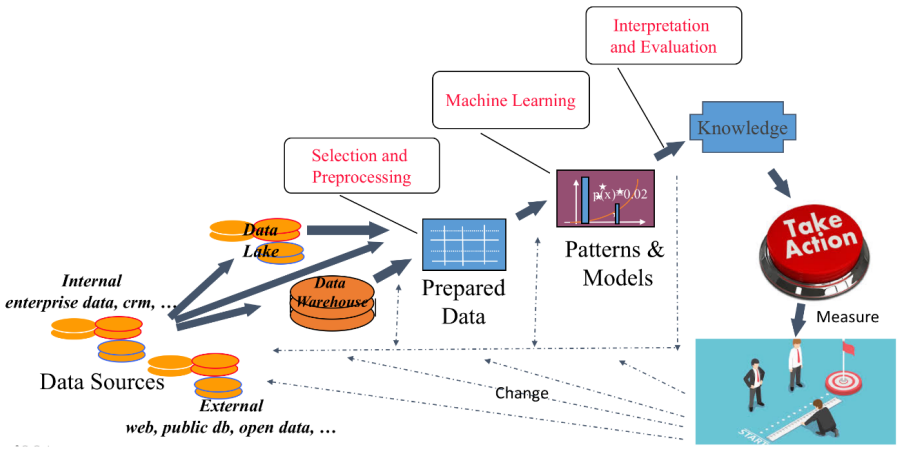



Figure 1.1: Data mining process

**Machine learning** Learning models and algorithms that allow to extract patterns from data. Machine learning

# 2 Business Intelligence

**Business Intelligence** Transform raw data into information. Deliver the right information to the right people at the right time through the right channel.

Business Intelligence

**Data Warehouse (DWH)** Optimized repository that stores information for decision making processes. DWHs are a specific type of DSS.

Data Warehouse

Features:

- Subject-oriented: focused on enterprise specific concepts.
- Integrates data from different sources and provides an unified view.
- Non-volatile storage with change tracking.

**Data Mart (DM)** Subset of the primary DWH with information relevant to a specific business area.

Data Mart

## 2.1 Online Analysical Processing (OLAP)

**OLAP analyses** Able to interactively navigate the information in a data warehouse. Allows to visualize different levels of aggregation.

Online Analysical Processing (OLAP)

**OLAP session** Navigation path created by the operations that a user applied.

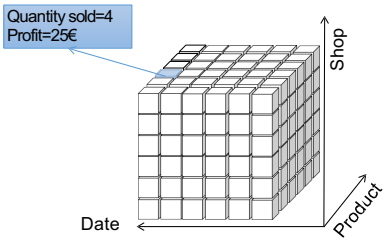
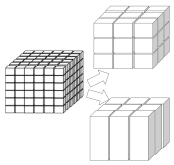



Figure 2.1: OLAP data cube

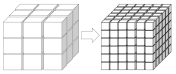
### 2.1.1 Operators

**Roll-up** Increases the level of aggregation (i.e. `GROUP BY` in SQL). Some details are collapsed together.



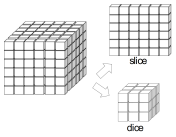
Roll-up

**Drill-down** Reduces the level of aggregation. Some details are reintroduced.



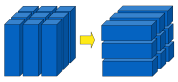
Drill-down

**Slide-and-dice** The slice operator reduces the number of dimensions (i.e. drops columns).
The dice operator reduces the number of data being analyzed (i.e. `LIMIT` in SQL).



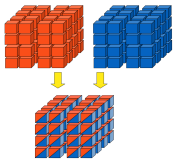

Slide-and-dice

**Pivot** Changes the layout of the data, to analyze it from a different viewpoint.



Pivot

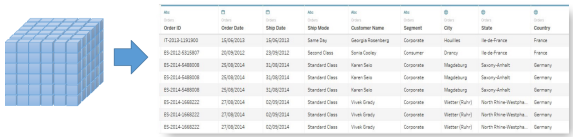
**Drill-across** Links concepts from different data sources (i.e. `JOIN` in SQL).



Drill-across

**Drill-through** Switches from multidimensional aggregated data to operational data (e.g. a spreadsheet).

Drill-through



## 2.2 Extraction, Transformation, Loading (ETL)

The ETL process extracts, integrates and cleans operational data that will be loaded into a data warehouse.

Extraction, Transformation, Loading (ETL)

### 2.2.1 Extraction

Extracted operational data can be:

**Structured** with a predefined data model (e.g. relational DB, CSV)

Strucured data

**Untructured** without a predefined data model (e.g. social media content)

Unstrucured data

Extraction can be of two types:

**Static** The entirety of the operational data are extracted to populate the data warehouse for the first time.

Static extraction

**Incremental** Only changes applied since the last extraction are considered. Can be based on a timestamp or a trigger.

Incremental extraction

### 2.2.2 Cleaning

Operational data may contain:

**Duplicate data**

**Missing data**

**Improper use of fields** (e.g. saving the phone number in the `notes` field)

**Wrong values** (e.g. 30th of February)

**Inconsistency** (e.g. use of different abbreviations)

**Typos**

Methods to clean and increase the quality of the data are:

**Dictionary-based techniques** Lookup tables to substitute abbreviations, synonyms or typos. Applicable if the domain is known and limited. — Dictionary-based cleaning

**Approximate merging** Merging data that do not have a common key. — Approximate merging

- **Approximate join** Use non-key attributes to join two tables (e.g. using the name and surname instead of an unique identifier).
- **Similarity approach** Use similarity functions (e.g. edit distance) to merge multiple instances of the same information (e.g. typo in customer surname).

**Ad-hoc algorithms** — Ad-hoc algorithms

### 2.2.3 Transformation

Data are transformed to respect the format of the data warehouse:

**Conversion** Modifications of types and formats (e.g. date format) — Conversion

**Enrichment** Creating new information by using existing attributes (e.g. compute profit from receipts and expenses) — Enrichment

**Separation and concatenation** Denormalization of the data: introduces redundances (i.e. breaks normal form[1]) to speed up operations. — Separation and concatenation

### 2.2.4 Loading

Adding data into a data warehouse:

**Refresh** The entire DWH is rewritten. — Refresh loading

**Update** Only the changes are added to the DWH. Old data are not modified. — Update loading

## 2.3 Data warehouse architectures

The architecture of a data warehouse should meet the following requirements:

**Separation** Separate the analytical and transactional workflows.

**Scalability** Hardware and software should be easily upgradable.

**Extensibility** Capability to host new applications and technologies without the need to redesign the system.

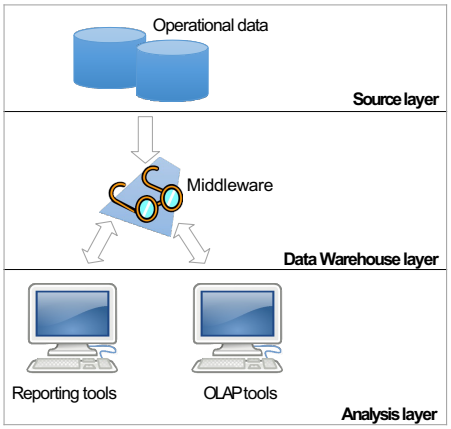
**Security** Access control.

**Administrability** Easily manageable.

[1] `https://en.wikipedia.org/wiki/Database_normalization`

### 2.3.1 Single-layer architecture

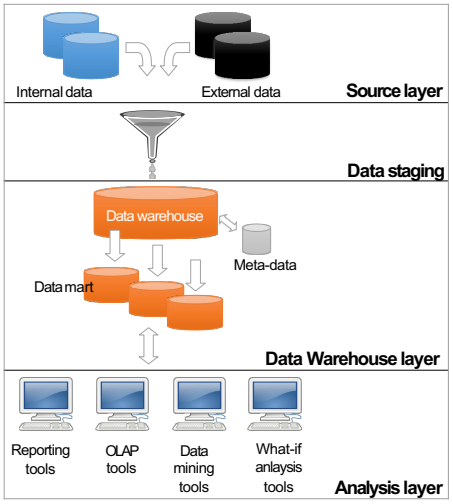
- Minimizes the amount of data stored (i.e. no redundances).
- The source layer is the only physical layer (i.e. no separation).
- A middleware provides the DWH features.




Single-layer architecture

### 2.3.2 Two-layer architecture

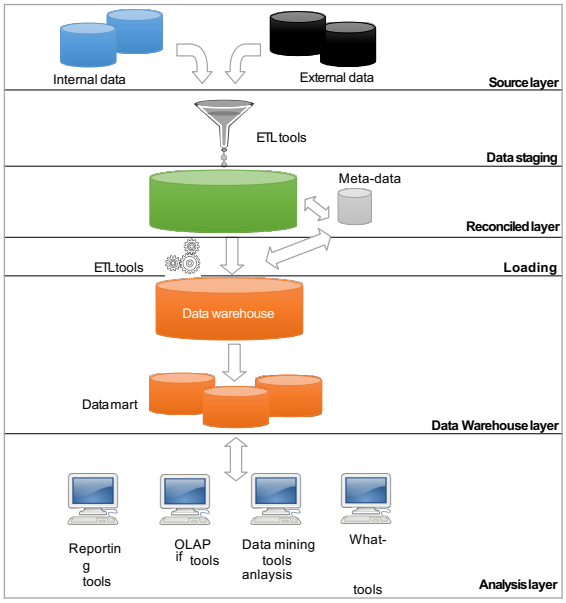
- Source data (source layer) are physically separated from the DWH (data warehouse layer).
- A staging layer applies ETL procedures before populating the DWH.
- The DWH is a centralized repository from which data marts can be created. Metadata repositories store information on sources, staging and data marts schematics.




Two-layer architecture

### 2.3.3 Three-layer architecture

- A reconciled layer enhances the cleaned data coming from the staging step by adding enterprise-level details (i.e. adds more redundancy before populating the DWH).




Three-layer architecture

## 2.4 Conceptual modeling

Dimensional Fact Model (DFM)

**Dimensional Fact Model (DFM)** Conceptual model to support the design of data marts. The main concepts are:

**Fact** Concept relevant to decision-making processes (e.g. sales).

**Measure** Numerical property to describe a fact (e.g. profit).

**Dimension** Property of a fact with a finite domain (e.g. date).

**Dimensional attribute** Property of a dimension (e.g. month).

**Hierarchy** A tree where the root is a dimension and nodes are dimensional attributes (e.g. date → month).

**Primary event** Occurrence of a fact. It is described by a tuple with a value for each dimension and each measure.

**Secondary event** Aggregation of primary events. Measures of primary events are aggregated if they have the same (preselected) dimensional attributes.

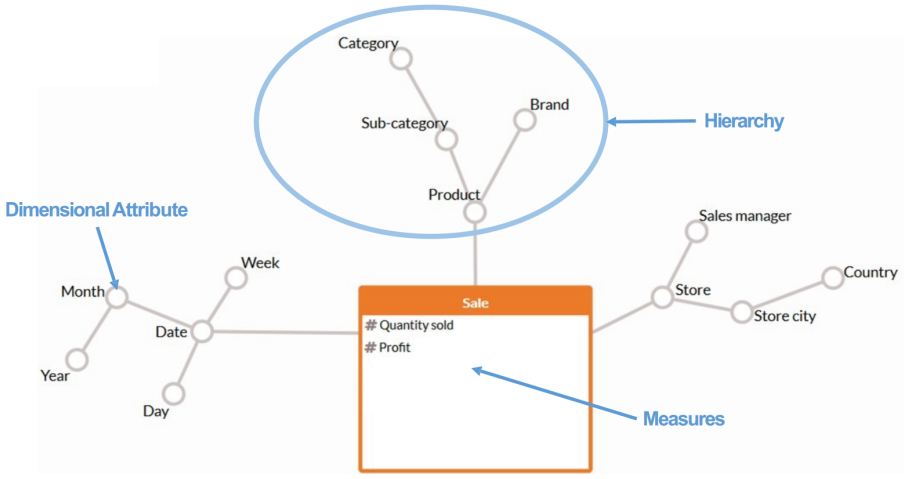



Figure 2.2: Example of DFM

Primary events

| Date | Store | Product | Qty sold | Profit |
|---|---|---|---|---|
| 01/03/15 | Central store | Milk | 20 | 60 |
| 01/03/15 | Central store | Coke | 25 | 50 |
| 02/03/15 | Central store | Bread | 40 | 70 |
| 10/03/15 | Central store | Wine | 15 | 150 |

SUM SUM

Secondary event

| Month | Store | Category | Qty sold | Profit |
|---|---|---|---|---|
| March 2015 | Central store | Food and Beverages | 100 | 330 |

Figure 2.3: Example of primary and secondary events

### 2.4.1 Aggregation operators

Measures can be classified as:

**Flow measures** Evaluated cumulatively with respect to a time interval (e.g. quantity sold). — Flow measures

**Level measures** Evaluated at a particular time (e.g. number of products in inventory). — Level measures

**Unit measures** Evaluated at a particular time but expressed in relative terms (e.g. unit price). — Unit measures

Aggregation operators can be classified as:

**Distributive** Able to calculate aggregates from partial aggregates (e.g. `SUM`, `MIN`, `MAX`). — Distributive operators

**Algebraic** Requires a finite number of support measures to compute the result (e.g. `AVG`). — Algebraic operators

**Holistic** Requires an infinite number of support measures to compute the result (e.g. `RANK`). — Holistic operators

**Additivity** A measure is additive along a dimension if an aggregation operator can be applied. — Additive measure

| | Temporal hierarchies | Non-temporal hierarchies |
|---|---|---|
| **Flow measures** | `SUM`, `AVG`, `MIN`, `MAX` | `SUM`, `AVG`, `MIN`, `MAX` |
| **Level measures** | `AVG`, `MIN`, `MAX` | `SUM`, `AVG`, `MIN`, `MAX` |
| **Unit measures** | `AVG`, `MIN`, `MAX` | `AVG`, `MIN`, `MAX` |

Table 2.1: Allowed operators for each measure type

### 2.4.2 Logical design

Defining the data structures (e.g. tables and relationships) according to a conceptual model. There are mainly two strategies: — Logical design

**Star schema** A fact table that contains all the measures and linked to dimensional tables. — Star schema

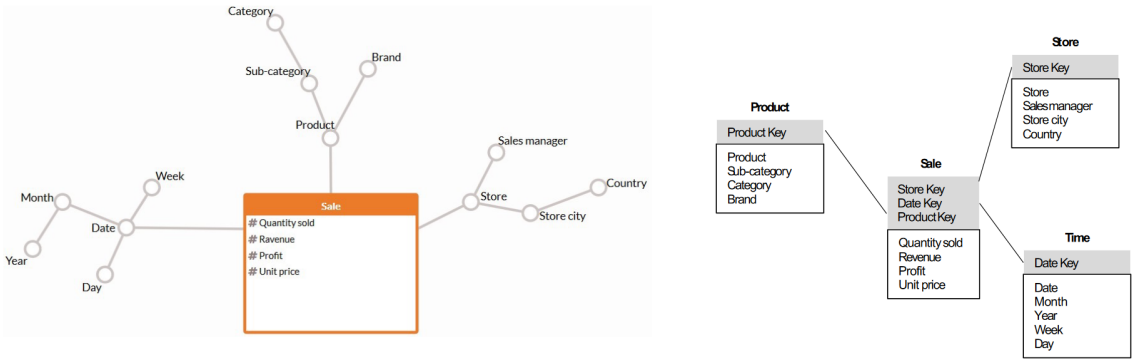



Figure 2.4: Example of star schema

**Snowflake schema** A star schema variant with partially normalized dimension tables. — Snowflake schema

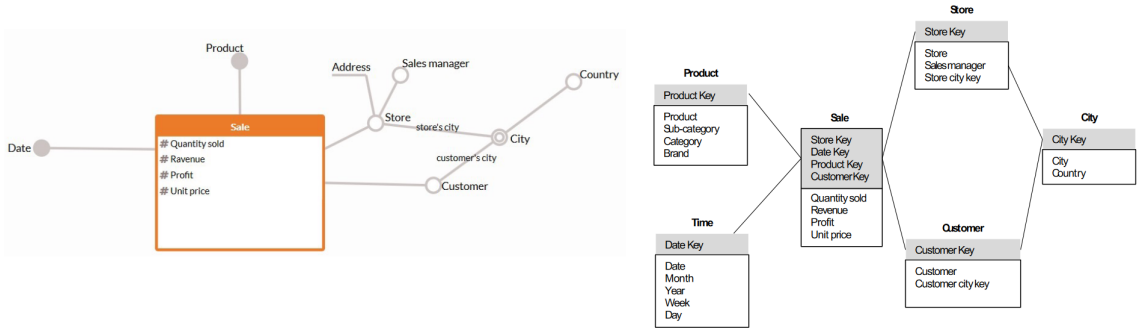



Figure 2.5: Example of snowflake schema